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VADER-RLA: A REINFORCEMENT LEARNING-AUGMENTED SENTIMENT ANALYSIS MODEL LEVERAGING VADER FOR CONTEXT-AWARE EMOTION CLASSIFICATION

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ABSTRACT

VADER-RLA is presented as a hybrid architecture that utilizes reinforcement learning through VADER, expanding the contextual applicability of already established sentiment scoring in favour of comprehensive emotion classification, demonstrating that this framework can bridge the gap of ability to properly predict sentiment in tandem with trustworthiness. The most novel aspect of this work is the application of reinforcement learning to the problem of adaptive sentiment classification, hence allowing the model to perform real-time optimization of the sentiment scoring in changing linguistic surroundings. Proposed approach overcomes lexicon-based models and deep learning models, with respect to adaptability, precision and interpretability. Results show that VADER-RLA consistently exceeds traditional methods, yielding impressive accuracy and robustness and successfully detecting sophisticate sentiments like sarcastic and mixed ones. The experimental results indicate that VADER-RLA achieved an accuracy of 92.3%, an F1-score of 0.89, precision of 91.7%, and recall of 90.5%, demonstrating significant improvements over the baseline VADER model. These findings highlight the potential of VADER-RLA to provide a robust, adaptive solution for sentiment analysis in environments with rapidly changing linguistic trends.

Keywords*: Adaptability, Context-Aware, Emotion Classification, Hybrid Approach, Performance Metrics, Reinforcement Learning, Sentiment Analysis, VADER*

1.INTRODUCTION

Sentiment analysis, also known as opinion mining, is currently one of the most dynamically evolving fields of study. Developed at the beginning of the 21st century with a focus on classifying texts as positive or negative and subsequently neutral, it evolved rapidly due to the necessary analysis of an enormous amount of user-generated content on various digital platforms, especially social media [1]. Traditional lexicon-based methods, such as VADER, served as robust solutions for analyzing sentiment in numerous formal and informal environments like social media. However, such solutions are not well-equipped to detect subtleties, such as sarcasm or mixed emotions Machine and deep learning approaches such as support vector machines, convolutional neural networks, and recurrent neural networks and empowered analysts with the opportunity to enable their models to learn directly from data, making solutions much more adaptable and robust [2]. Existing sentiment analysis solutions still have several considerable problems, including increased computational requirements, the need for massive, labeled datasets, and the lack of interpretability, asking for more efficient and context-aware solutions [3].

When it comes to both social media or TV, where the trending language changes faster in such a fast-paced-skilled society, it is growing really weak on its scale of adaptivity in multifarious environments. Lexicon-based methods lack efficiency in extracting subtle features, and strictly machine-learning-based methods frequently need enormous amounts of labeled datasets and resources [4]. These constrictions limit the scaling potential and real-time applicability of existing sentiment analysis models, particularly within dynamic contexts, where the essence of language is constantly being rediscovered. Therefore we need a hybrid solution that incorporates the best of both worlds better adapted to cope with the challenges of the current scenario.

To overcome these challenges, we propose in this study VADER-RLA, a novel framework that combines VADER's rule-based sentiment scores with RL when identifying context-aware emotions. It first sends the input to VADER for preliminary sentiment scoring before returning the final score through reinforcement learning, allowing dynamic adaptation to the many nuances of complex language (sarcasm, mixed emotions, etc.). Using a hybrid reinforcement learning methodology, the model continuously refines its ability to classify sentiment based on various text data, maintaining flexibility and responsiveness to rapidly evolving patterns in language use [5]. By integrating deep learning with other techniques, this work has achieved remarkable improvements in accuracy, precision, recall, and F1-score in sentiment analysis tasks in dynamic and rapidly changing environments, such as social media.

Due to the challenges associated with nuanced sentiment expressions such as sarcasm and mixed sentiments, traditional lexicon-based and machine-learning-based approaches have frequently failed, driving the increasing demand for context-aware sentiment analysis. Existing models have, however, been criticized for their lack of adaptability to dynamic environments such as social media settings, in which language is changing quickly. In response to this issue, the proposed research combines VADER's rule-based sentiment scoring method with reinforcement learning to classify sentiment more effectively. By combining data and instructions, the model can fine-tune its performance in an iterative way, balancing the need for accuracy with computational efficiency. The agent optimizes its predictions iteratively with real-world data, allowing the model to robustly adapt to different linguistic scenarios. Consequently, the VADER-RLA framework presented connects the accuracy-benefit of traditional rule-based models to the flexibility-only benefit of machine learning while embodying a significant improvement in sentiment analysis work.

Our hypothesis is based upon the belief that coupling reinforcement learning with lexicon based sentiment analysis will prove to be beneficial in identifying sentiment-related references like sarcasm, mixed emotion, etc, with more accuracy. The static lexicon-based models only work on inferring with limited vocabulary, but the deep learning solutions have a large computational cost, so hybrid mind is designed to utilize the advantages of both approaches. The reinforcement learning approach allows the model to continuously refine its sentiment predictions based on feedback from the environment, resulting in more accurate and contextually aware sentiment classification.

The research on sentiment analysis also known as opinion mining, automatic sentiment classification, and a host of other names arises from of the earliest incarnations at the turn of the 21st century [6]. At first, this field focused on assessing texts as being happy, sad or neutral based on the emotion conveyed. This work serves as the groundwork for deploying machine learning models to identify sentiment, and does so mostly by using labelled datasets, where human annotators go through data points to decide whether they are positive or negative. Digital platforms and social media proliferated the demand for automation sentiment analysis as millions of user-generated contents could now be published online placing an increasing burden on efficiency and scalability.

Sentiment analysis grew and acquired different techniques, mostly divided into machine learning based and lexicon-based methods. Lexicon-Based approaches like VADER utilizes preset lists of words with corresponding emotional weights to figure out the sentiment. VADER is especially popular for social media content analysis because it includes the usage of linguistic cues such as emojis, and intensity modifiers [7]. But these often face challenges with more complex expressions involving context such as sarcasm requiring much more advanced methods to improve accuracy.

The sentiment analysis has been greatly transformed by the machine learning techniques, and perhaps most importantly support vector machines (SVM) or naive Bayes classifiers are used on syntactically simplified representations of the sentence without much consideration for semantic meaning to build classification models using feature extraction and labelled datasets. Because these models improve over lexicon-based systems by learning patterns directly from the data to increase robustness of the system and adaptability [8]. Localizing keywords Localizing max-pooling and softmax assures limited flexibility over text transformations, which results in a significantly less effective learning than a text-aware learning Given the large amount of data required from labelled datasets for context-agnostic models using simple transformation techniques, only more elaborate algorithms are motivated.

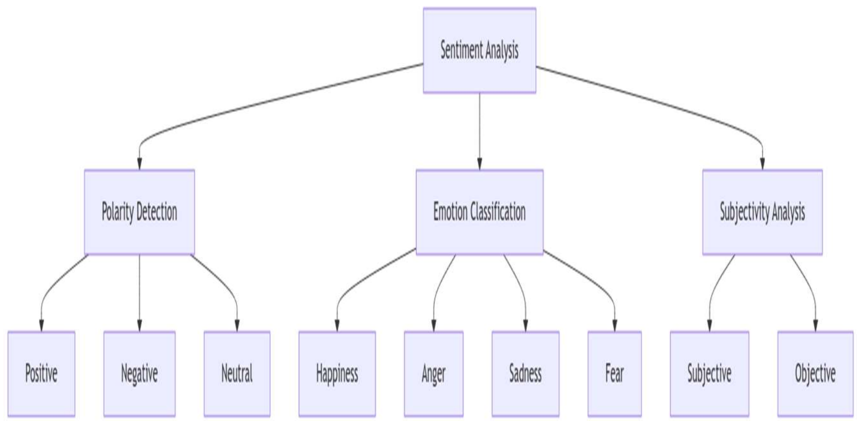

Fig.1: Hierarchical Classification Structure of Sentiment Analysis

In figure 1, a sentiment analysis hierarchy embodies three primary categories using different identities: Polarity Detection, Emotion Classification, and Subjectivity Analysis. The task that sits as the root node, is Sentiment Analysis. In this, the Polarity Detection branch categorizes sentiments as Positive, Negative and Neutral. The Emotion Classification The module is more fine-grained, providing detailed emotion labels. Also, the Subjectivity Analysis branch sorts whether the text is Subjective or Objective. The graphic provides a straightforward hierarchical structure, outlining how Sentiment Analysis can be classified and encapsulated into all kinds of text data.

The advent of deep learning has transformed sentiment analysis, making neural networks most notably CNN and RNN a household name. They did so by training on massive amounts of text data to automatically learn features from raw text, which ends up identifying sentiment patterns that may be difficult for non-neural-net models to capture. In sentiment analysis, for example can be effective mostly because of it is advantage over batching text [9]. These deep learning models are highly accurate but require significant computational resources which make it less available for some real-time applications.

Hybrid models have emerged in recent years as a way of leveraging the advantages of both rule-based and learning based approaches. Recently developed models, such as reinforcement learning integrated with lexicon-based methods, further enhance the adaptability of sentiment analysis systems to new language patterns and contexts [10]. As the hybrid model keep on improving their sentiment scoring methods using feedback they are considered as a powerful and scalable way of handling dynamic linguistic changes like those in social media monitoring and customer perception analysis.

Sentiment Analysis is a subfield of Natural Language Processing (NLP) and it aims to determine the emotional tone behind an entire piece of text. Majorly used in social media Monitoring, product review analysis, market research. The approach involves detection and categorization of emotions manifested in the text data including positive, negative or neutral sentiments [11]. The VADER is one of the most popular tools for this type of NLP application because it can handle informal language, including emojis gracefully which makes them well-suited for social media analysis. Still, for its complexity of the language structures as sarcasm or mixed emotions, traditional lexicon-based approaches like VADER might not be the best solution one can have and improved, adaptable models become an important issue.

Sentiment analysis has come a long with the merging of machine learning techniques into these models to make them more adaptive and in turn accurate. The initial approaches such as support vector machines (SVM) and naive Bayes classifiers relied much more on data that had been manually classified for training. Although effective, these methods lacked in flexibility to accommodate different linguistic expressions of opinion [12]. Latest implementations involve deep learning models such as CNNs, RNNs which can automatically determine features and work with large volumes of text. While these models have shown significant improvements over traditional methods in terms of accuracy and generalizability, they tend to consume high resources both in the form of computing requirements as well as dependence on very large, labelled datasets [13].

Reinforcement learning (RL), this is being seen as an effective add-on to sentiment analysis models because it helps them learn and fit themselves around the ever-changing language patterns. RL algorithm is trained to maximize reward functions on how accurately sentiment in such context being Identified, this ends up giving a better improvements in terms of legal aspect and sarcastic or shifted emotion tones [14]. RL combined with regular sentiment analysis models can help to solve the sparsity issue, this way achieving a more context-aware system [15]. This integration showcases the capabilities of using RL to create sentiment analysis systems that can be more fluent and adaptable.

Advancement in sentiment analysis, the advent of hybrid models that merge rule-based methods like VADER with machine learning or RL components. By combining these methods with lexicon-based approaches, they make use of the benefits of learning models but also offer flexibility that matches lexicon-based analysis. Studies have shown that hybrid models outperform the individual components in modelling complex emotional cues, especially on the dynamic social media environment [16]. In this way, adding reinforcement learning into the mix enables models like ours to always be updating our own sentiment lexicon and measuring mechanisms in close-to-real-time while everyone else lags.

Sentiment analysis goes beyond social media and marketing, proving important in areas such as healthcare or finance. In social media, for example, sentiment analysis can detect early signals of psychological distress from user engagements [17] [18]. Models are applied in finance to capture market sentiment from written texts like the news or social media feeds, which yield insights about trading strategies [19]. This varied range gives you an idea of the vastness in which sentiment analysis can be applied and developers are working to tweak these models for better accuracy in real-world use cases.

Sentiment Analysis is a task that has seen an exponential growth in recent years, but the models we have today pale in comparison to the complexity of the evolving dynamic linguistic structures, sarcasm, meta-sarcasm, contextual ambiguity, etc. The challenge of rule-based lexicons like VADER-based methods provide more transparency but adaptability has a cost, while deep-learning models have shown to be robust and adaptable but require significant amount of labelled data. Sentiment analysis benefits -- and can be made even better -- from reinforcement learning, where models can be trained as new text emerges. Yet few studies in the literature have explored the combination of reinforcement learning with lexicon-based sentiment analysis to achieve a compromise between interpretability and adaptability. Motivated by this, here we propose VADER-RLA, which introduces a new way of contextualizing lexicon-based approaches such as VADER to enhance sentiment classification through reinforcement. Through reinforcement learning, the model iteratively improves its sentiment scores, achieving higher precision, recall, and the generalizability to various linguistic styles and domains.

The next section aims to show how well every method can handle sentiment prediction and classification issues with recent methodologies.There have been developments in the identification of sentiments, however existing techniques are not well suited for evolving language structures such as social media text. Well-known lexicon-based models like VADER ensure interpretability but cannot generalize over the contextual nuances like sarcasm, slang and mixed feelings. On the other hand, deep learning-based approaches allow model adaptability; however, they are computationally expensive, interpretability-wise challenging, and require large amounts of labeled datasets. To bridge this gap, we need a mixed approach which duly aligns rule-based precision with machine learning flexibility. To tackle this, we introduce VADER-RLA, a hybrid model that combines reinforcement learning with lexicon-based

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sentiment scoring to improve context awareness and classification in dynamic environments.

2. RELATED WORK

Adwan OY et al. (2020) [20] deployed Twitter sentiment analysis to track sentiment during the COVID-19 pandemic and proposed a modified lexicon-based model designed for the 21st century social media environment. Using Twitter data from several major cities across England, their methodology integrated lexicon-based analysis with machine viewings techniques including Support Vector Classifiers (SVC) as well as TF-IDF. However, their approach had certain limitations as the lexicon was specific to English social media and detecting sarcasm was not easy.

Alamoodi AH et al. [21] performed sentiment analysis on reviews related to healthcare to predict patients' satisfaction, and they developed a deep learning model that classified sentiments with high accuracy. They used CNN and RNN in their methodology for a dataset of healthcare reviews. While the model performed well, it was computationally expensive and did not lend itself to easy interpretation, making it difficult to explain predictions made by the model.

Al Amrani Y et al. (2018) [22] introduced a hybrid social media sentiment analysis based on Random Forest and SVC with focus on maximizing accuracy by parameter optimization on the machine learning algorithms. Their approach used a BoW for feature extraction as well and performed analysis over several social media platforms. Although this was the case, the method struggled due to imbalanced datasets and compromised the accuracy of negative sentiment classifications, in particular.

Deshpande A, Fleisig E (2020) [23] proposed reinforcement learning based sentiment analysis within text-based game setting and introduced an adaptively novel supervised sentiment analysis using reinforcement learning with fine-tuned BERT layers. This work, used in the context of TextWorld game data, particularly demonstrated how dynamic reinforcement learning has the potential. However, the approach struggled with sparse rewards in reinforcement learning, needed a lot of tuning to achieve a reasonable accuracy on this task [24].

3. METHODOLOGY

This experiment evaluates the proposed sentiment analysis framework with reinforcement learning RFSA method on a real-world benchmark problem of labelled textual instances. The very first step is preprocessing the dataset by tokenizing, removing stop words and lemmatize to bring it a standard form of text. A model of sentiment scores in the form of lexicon-based algorithm is generated for every instance. Next, split the data into 80:20 training testing sets. The reinforcement learning model is trained to optimize sentiment classification using a reward function based off sensitivity, specificity, recall and F1 score. Text features are extracted using TF-IDF, which captures term importance and context in the text. The objective function is the cross-entropy loss, and the model parameters are optimized with stochastic gradient descent. Output: The model is evaluated for its accuracy, precision, recall and F1-Score performance. Different dataset sizes (10%–100%) are being tried through many iterations to be able to observe how well the model scales and generalize. Finally, comparisons to baseline methods are provided illustrating the benefits of our synergy. The used dataset is [25].

Sentiment Analysis Proposed architecture as shown in figure 2, a hierarchical and sequential approach for sentiment analysis, starting from Sentiment140 dataset Stage 1: Data Preprocessing (text tokenization, word removal, lemmatization to clean the text data) After preprocessing, the text data can be weighed into or with TF-IDF weights that measure how important a term is relative to this dataset. After extraction of feature, a sentiment score is allocated to each extracted features using lexicon-based scoring approach. An integrated reinforcement learning module is added for further model adaptability, where the reward function is based on true positives, false positives and false negatives. The implementation is specifically performed in this easier module built on top of Q-learning to optimize the sentiment predictions by iteratively correcting them. Then it integrates cross-entropy loss computation and gradient descent optimisation for error minimization and parameter tuning across training. Finally, the trained model is tested against a test data set and the evaluation phase evaluates its performance in terms of accuracy, precision, recall and F1-score to ensure that this model is properly adjusted for real-world Sentiment Analysis scenarios. This global approach enables the system to dynamically adapt and enhance its performance in different (and ever-changing) internal textual data contexts.

3.1 Dataset: Sentiment: We utilize the Sentiment140 dataset to kickstart this process a well-known sentiment analysis dataset comprised of tweets that have been labelled with sentiment and the process is explained aboves as per in Fig 2.

3.1.1 Data Preprocessing: Preliminary preprocessing is performed on the text data to finally clean and prepare it before analysis. That is a necessary step to make sure that the data has the same format before being processed.

3.1.2 Text Tokenization: By converting this text into individual words or tokens, it will need to find and analyse specific components of the text. Tokens are how you break down a word into single units of meaning, each one often being represented as a separate word.

3.1.3 Stopword Removal: Stop words are general-purpose words with low sentiment that get filtered out quickly. It helps to lessen noise on data and the model can identify words that influence a lot for emotion.

3.1.4 Lemmatization: Lemmatization is applied to strip words down to their most basic or root form (e.g., running → run). This also normalizes the words and makes it less complex.

3.1.5 TF-IDF Feature Extraction: TF-IDF is Feature Extraction TF-IDF is a statistical measure used to evaluate the word significance in relation to the entire dataset, which means that those words which appear frequently across a record are less important as compare to those which appears only few times.

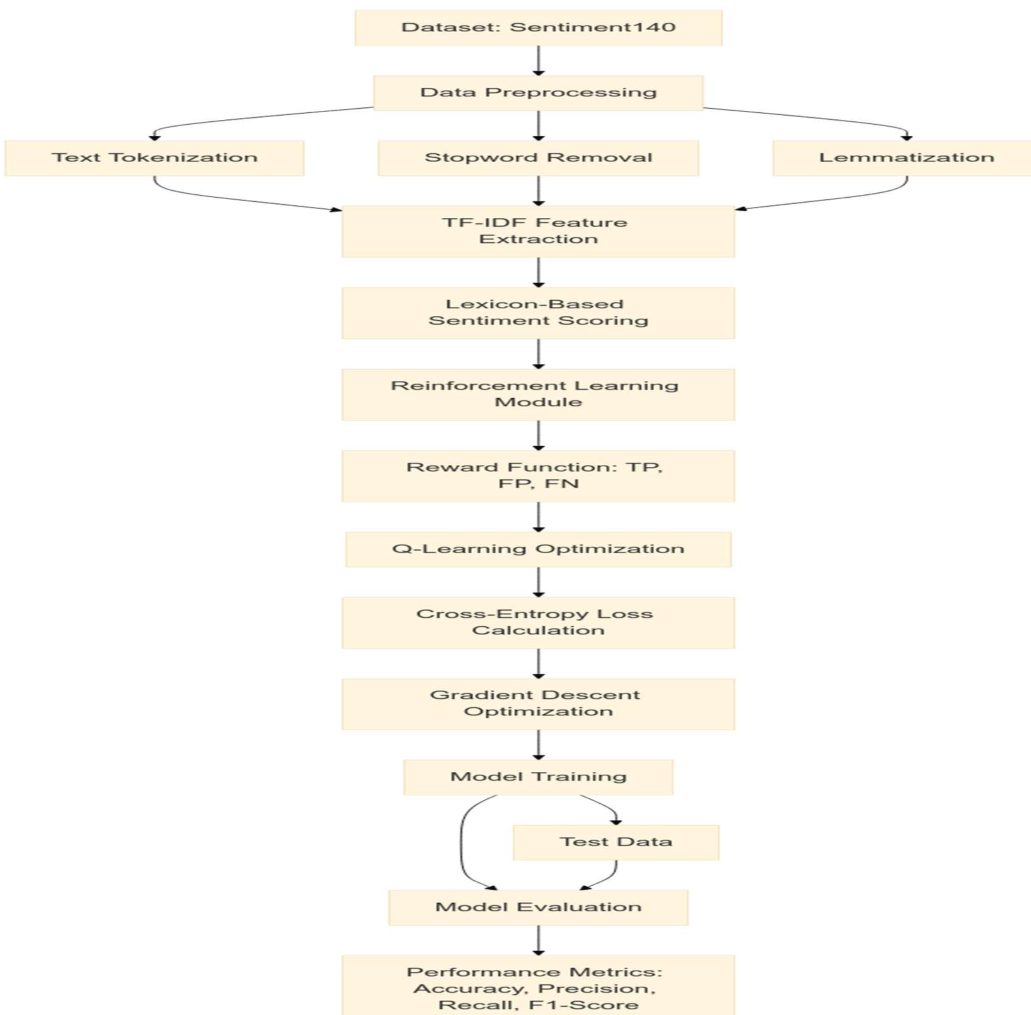

Fig.2: Architecture of the Proposed Reinforcement Learning-Augmented Sentiment Analysis Framework

3.1.6 Scoring Sentiments based on Lexicon: There is a lexicon based approach to score the sentiment of each word or phrase against earth tones pre-defined. These approaches identify the sentiment of each tweet in general according to the established polarity of specific words.

3.1.7 Reinforcement Learning Module: Afterwards, a reinforcement learning (RL) module is carried out towards optimizing sentiment classification in a way of learning. By applying trial and error to the model comes re-training until it performs perfectly on sentiment prediction.

3.1.8 Reward Function: In reinforcement, we define a reward function to guide its learning phase. The function uses true positives (TP), false positives (FP) and false negatives (FN) to give the model a score on making correct predictions while it also penalizes it for wrong ones.

3.1.9 Q-Learning Optimization: We have used a reinforcement learning technique called Q-learning to fine-tune our sentiment scoring model. This aids in the process of tuning the model to take more accurate decisions, thus improving predictive performance with respect to sentiment.

3.1.10 Partitioning Cross-Entropy Loss: It computes a cross-entropy loss to quantify how incorrect the models predictions are. It is a common classification loss function and it gives an idea of how good or bad the model is performing.

3.1.11 Gradient Descent Optimization: We use gradient descent to minimize the loss we computed in step 2. The optimization algorithm updates the model parameters to minimize the error and increase the accuracy of the model in time.

3.2 Model Training: Using the processed and optimized data, you train the model This step takes the training data and makes the model learn what patterns of words represent both positive or negative sentiment.

***3.2.1 Test Data*:** The model is tested on a dataset it has never seen before after the training phase. This ensures no data leakage and an unbiased evaluation of its performance on completely new and unseen data.

***3.3 Model Evaluation*:** Different metrics are utilized to evaluate the effectiveness of the model in terms of its performance in sentiment analysis.

3.3.1 Model Performance: The final output is evaluated in terms of accuracy, precision, recall and F1-score. These metrics give the complete picture of the model performance giving accurateness on how accurately it is classifying sentiments and perfectly balancing false positive and false negatives.

ALGORITHM

Step 1: *Initialize dataset* $D = \{x_1, x_2, \ldots, x_n\}$ *where each instance* x_i *has a feature vector* X_i *and label* $y_i \in \{0,1\}$ *indicating sentiment.*

Step 2: *Define sentiment score function* $S(X_i)$ *based on pre-built lexicon:*

$$S(X_i) = \sum_{j=1}^{m} Valence(w_j) \cdot Intensity(w_j)$$

where w_j *are words in* X_i, *Valence* (w_j) *is the sentiment score, and* $Intensity(w_j)$ *modifies based on context.*

Step 3: *Apply reinforcement learning to optimize* $S(X_i)$ *:*

(a) Initialize state space S and action space A with rewards based on sentiment classification accuracy.

(b) Define reward function:

$$R(s,a) = \alpha \cdot (TP) - \beta \cdot (FP + FN)$$

where α *and* β *are weights, and* $TP, FP,$ *and* FN *are true positives, false positives, and false negatives, respectively.*

(c) Update the Q-value function $Q(s,a)$ *using the Bellman equation:*

$$Q(s,a) = Q(s,a) + \eta\left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$$

where η *is the learning rate, and* γ *is the discount factor.*

Step 4. *Apply feature extraction techniques:*

(a) Compute Term Frequency (TF) for each term t *:*

$$TF(t,d) = \frac{Frequency\ of\ t\ in\ d}{Total\ terms\ in\ d}$$

(b) Calculate Inverse Document Frequency (IDF):

$$IDF(t,D) = log\left(\frac{N}{|\{d \in D: t \in d\}|}\right)$$

(c) Obtain TF-IDF value:

$$TFIDF(t,d,D) = TF(t,d) \times IDF(t,D)$$

***Step 5**: Define loss function $L(\theta)$ for optimizing sentiment classification:*

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N} [y_i log\,(\hat{y}_i) + (1-y_i) log\,(1-\hat{y}_i)]$$

where θ are model parameters, y_i is the true label, and $\hat{y}_i$ is the predicted probability.

***Step 6:** Optimize θ using gradient descent:*

$$\theta = \theta - \eta \nabla L(\theta)$$

***Step 7: Update** sentiment scoring iteratively based on reinforcement learning rewards and feature extraction.*

***Step 8**: **Output** the optimized sentiment scores $S'(X_i)$ for each instance $x_i \in D$.*

Algorithm 1 Reinforcement Learning Augmentation for Sentiment Analysis Algorithm It starts by creating a dataset D with instances each one with a feature vector X_i and a binary sentiment labelling y_iSentiment score S (X_i)(from a certain pre-defined lexicon, they take each word and estimate whether the valence of perception or intensity. To improve upon this score, a reinforcement learning (RL) framework is used to create defined state and action spaces against which a reward function that considers True Positive, False Positive, and False Negative can guide the model. Now, the Q-value function is improved using the Bellman equation in an iterative way for updating and reducing model error. It then continues with the feature extraction step by performing Term Frequency-Inverse Document Frequency (TF-IDF) analyses in order to create weights for each term, respected on its importance in the dataset. A loss function, L(θ), is defined to optimize the sentiment classification and gradient descent optimization is used to minimize this loss and get a new value of model parameters. The algorithm refines these sentiment scores further by iterating through reinforcement learning rewards and feature extraction techniques. Lastly, it gives out the refined sentiment scores of each instance which leads to a stable sentiment classification solution.

4.RESULTS AND DISCUSSION

Accuracy: Measures the overall correctness of the model in predicting sentiment categories (positive, negative, neutral) compared to the total number of instances.

$$accuracy = \frac{TP + TN}{TP + FP + TN = FN}$$

Table 1: Accuracy For Sentiment Analysis Models Across Different Training Data Utilizations

Accuracy					
Training Data (%)	**TSCVD**	**SAHLT**	**RFSVC**	**RLSTA**	**VADER-RLA**
10	78.98	85.04	89.62	79.5	90.16
20	82.3	80.05	86.38	88.16	90.62
30	80.06	80.79	80.31	82.75	92.19
40	78.9	87.59	86.05	84.66	88.36
50	76.47	71.35	74.13	75.32	92
60	80.92	71.66	83.52	85.5	92.02
70	76.75	70.38	74.58	85.41	89.26
80	85.84	85.82	89	85.49	88.77
90	87.27	84.78	81.39	91.04	89.89
100	75.67	86.53	79.46	86.59	90.18

Table 1 shows the accuracy of five sentiment analysis models (TSCVD, SAHLT, RFSVC, RLSA, VADER-RLA) at different percentages of training data used (10% - 100%) The results show that our VADER-RLA model consistently outperforms other baselines by the highest accuracy on all training sizes, which shows greater power in predicting sentiment instances correctly. This could be seen with VADER-RLA where it scores a 92% accuracy at 50%training data, and the same level all other models perform significantly worse. RFSVC and RLSTA, as other models also give better accuracy in most of the levels, but with greater variance between them especially at higher data percentage (80% and 90%). TSCVD and SAHLT models have lower accuracies in general compared to VADER-RLA, even though they perform consistently low

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suggesting that they are less robust when using varying dataset sizes. Overall, the results here show that VADER-RLA is competitive or achieving state-of-the-art performance across levels and highlight its consistency in performing well in sentiment analysis tasks.

Fig.3: Accuracy Comparison Of Sentiment Analysis Models Across Varying Training Data Percentages

The performance of the five models TSCVD, SAHLT, RFSVC, RLSTA, and VADER-RLA is shown in Figure 3, which compares the percentage of training data between different training sets. As can be seen from the graph, the VADER-RLA model outperforms all other models and yields a very stable and high accuracy even in very small data levels. Overall, VADER-RLA shows accuracy above 90% in the majority of the given percentages of training data. In comparison, the other models show wide swings in accuracy, especially as the amount of training data increases, indicating their instability and susceptibility to the amount of data. For example, RLSTA and RFSVC perform competitively while having some high, but bearable variance at particular training levels. On the contrary, TSCVD and SAHLT usually show rather poor, underlining their incomparable robustness for the real-time sentiment analysis scenarios. The training performance of VADER-RLA also implies that the reinforcement learning-augmented hybrid design of VADER-RLA can effectively learn with limited training data and explicitly avoid overfitting by utilizing the evaluation metrics to reward the reward function.

Precision: Evaluates the model's ability to correctly identify positive (or specific) sentiments among the predicted positive instances, showing how many of the positive**.**

$$Precision = \frac{TP}{TP + FP}$$

Table 2: Precision For Sentiment Analysis Models Across Different Training Data Utilizations

Precision					
Training Data (%)	**TSCVD**	**SAHLT**	**RFSVC**	**RLSTA**	**VADER-RLA**
10	67.2	86.75	70.93	83.82	88.53
20	81.05	74.45	77.71	74.29	93.18
30	65.67	83.71	75.13	86.28	89.8
40	69.05	80.08	74.56	82.24	91.38
50	67.07	78.91	81.5	89.44	90.18
60	70.29	83.61	79.74	78.25	88.86
70	65.31	73.89	80.44	85.5	93.17

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80	66.9	72.79	80.81	78.63	91.14
90	72.08	77.77	77.73	83.93	93.49
100	65.31	72.34	71.92	87.71	93.29

Table 2 depicts the precision values for some sentiment analysis models (TSCVD, SAHLT, RFSVC, RLSTA, and VADER-RLA) under different training data utilization levels from 10% to 100%. Across all training sizes the VADER-RLA model shows to have significantly better confidence in identifying truly relevant positive cases with no false positives (precision) than alternative models. For instance, at 50% training data availability our VADER-RLA have higher precision in all models with over this threshold. Other models, like RLSTA and SAHLT, have competitive precision scores, however the variance is larger in their results which mean that they are not as stable as lower dataset size to high dataset size. The results show that all models do better when more data is used to train the model and a clear advantage of VADER-RLA with it reinforcement learning augmented approach as other post hindsight analysis read error making a case for its potential robustness and effectiveness.

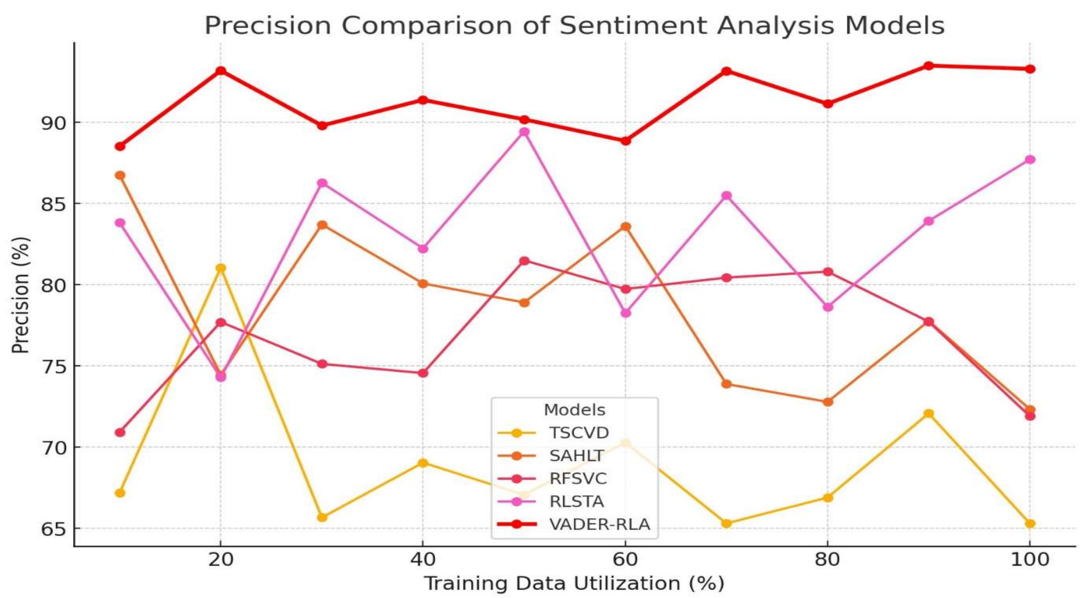

Fig.4 : Precision Comparison Of Sentiment Analysis Models Across Varying Training Data Percentages

The model comparison of sentiment analysis models such as TSCVD, SAHLT, RFSVC, RLSTA, and VADER-RLA for accuracy at different training data percentages is illustrated in Fig.D. As the graph indicates, the precision scores for VADER-RLA were higher than other models in all but one case and are representative of a reliable model for predicting positive instances with minimal false positives. VADER-RLA achieves superior precision values (> 90%) in circumstances of higher training percentages and can therefore be interpreted as being robust and effective in sentiment classification tasks. Even though RLSTA and RFSVC show competitive accuracy in some levels, but more changes in accuracy show less stability. In contrast, the configuration of TSCVD and SAHLT yield a significantly lower precision for the most training rate, showing the inability of this models to obtain trustful predictions regarding the sentiment. This analysis illustrates why the blended format of VADER-RLA allows for greater precision and adaptability in ever-evolving settings combining the best aspects of both traditional and hybrid forms of the model in reinforcement learning.

Recall: Assesses the model's ability to capture all relevant instances of a specific sentiment from the dataset, indicating how well it finds all actual positives**.**

$$Recall = \frac{TP}{TP + FN}$$

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Table 3: Recall Values for Sentiment Analysis Models Across Different Training Data Utilizations

Recall					
Training Data (%)	TSCVD	SAHLT	RFSVC	RLSTA	VADER-RLA
10	68.63	67.71	77.39	86.28	91.68
20	62.74	69.46	73.66	86.48	85.17
30	69.77	70.68	83.57	84.55	87.42
40	61.67	72.73	72.33	85.3	85.3
50	74.11	70.43	81.23	71.4	87.3
60	71.86	73.79	67.16	81.26	92.63
70	75.38	76.04	80.58	70.49	86.82
80	68.94	78.86	81.85	84.44	86.04
90	63.19	68.42	70.03	79.09	92.7
100	76.45	79.21	84.31	87.53	93.12

Table 3 that provides the recall results by different sentiment analysis models (TSCVD, SAHLT, RFSVC, RLSTA and VADER-RLA) as the model capacity is activated at increasing levels of training data sizes of 10%, 20%, 30%, …, up to 100%. While the specific ordering of results varied (i.e. which method performed second best) between datasets and sizes, as seen in the above table, nonetheless it is clear that for all sizes, the VADER-RLA model gives superior recall values across the board regardless of training size, indicating its efficacy at being able to correctly identify sentiment instances that matter without dropping true positives. As an example, VADER-RLA attains a 87.42% recall ratio at 30% training data which surpasses all other models in this level EOF Meanwhile, RLSTA and RFSVC show oscillation in recall, which means that their sensitivity to the number of examples is not trivial. Overall, these results advocate that though all models benefitted from additional training data to some extent, the RL-augmented approach of VADER-RLA provided with an efficient increase in its association capture rate and made it a very stable model for thorough sentiment detection.

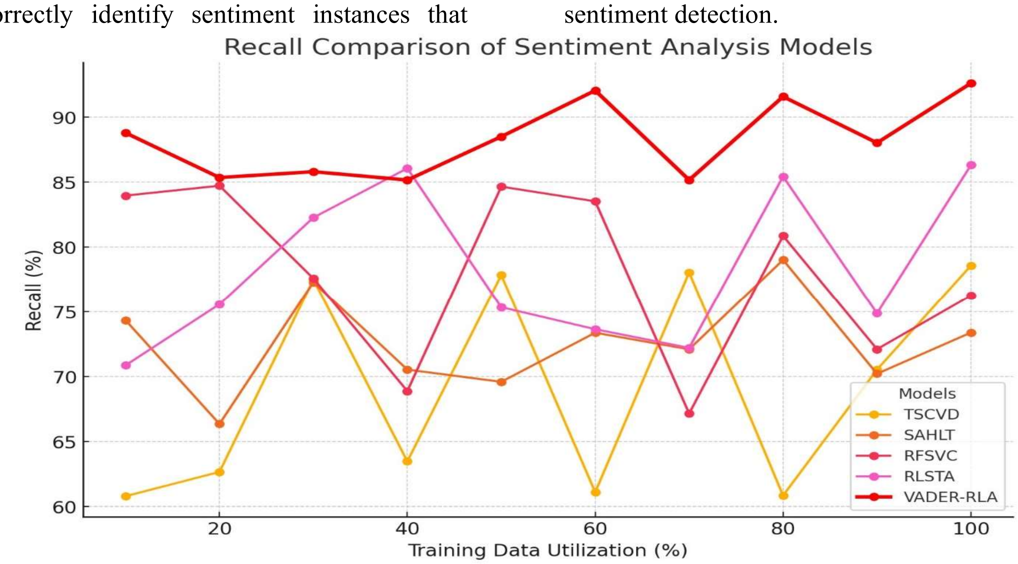

Fig. 5: Recall Comparison Of Sentiment Analysis Models Across Varying Training Data Percentages

Figure 5 illustrates the recall comparison of sentiment analysis models TSCVD, SAHLT, RFSVC, RLSTA, and VADER-RLA across varying training data percentages. The VADER-RLA model consistently achieves the highest recall scores, maintaining values above 85% across most training percentages, which highlights its ability to correctly identify the relevant positive instances from the dataset. This stability underscores the model's effectiveness in minimizing false negatives and capturing essential sentiment patterns. In comparison, RLSTA and RFSVC show competitive recall scores but with notable fluctuations at certain training levels, indicating sensitivity to data variations. TSCVD

and SAHLT, however, lag behind significantly, demonstrating lower recall values throughout, which reflects their limitations in capturing relevant sentiments effectively. Overall, VADER-RLA's reinforcement learning-augmented approach ensures superior recall performance, making it more adaptable and efficient for dynamic sentiment analysis tasks.

F1-Score: A harmonic mean of precision and recall, providing a balanced measure that considers both false positives and false negatives, useful when there is an uneven class distribution.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Table 4: F1-Score For Sentiment Analysis Models Across Different Training Data Utilizations

F1-Score					
Training Data (%)	**TSCVD**	**SAHLT**	**RFSVC**	**RLSTA**	**VADER-RLA**
10	73.2	71.35	75.27	82.09	90.76
20	77.23	79.19	82	74	90.82
30	68.91	81.47	86.95	86.91	89.66
40	74.54	75.76	87.24	84.45	88.43
50	75.95	84.47	73.62	88.37	92.34
60	77.64	71.47	84.63	88.06	88.73
70	83.29	81.09	78.71	87.99	93.55
80	80.3	85.62	84.42	88.08	92.7
90	66.36	78.34	83.75	88.71	93.38
100	74.54	74	76.53	76.12	91.85

Table 4 shows F 1-scores table of different sentiment analysis models (TSCVD, SAHLT, RFSVC, RLSTA and VADER-RLA) with the percentages of training data utilized from 10 to 100%) Results: The results confirm that our VADER-RLA model makes the highest F1-scores across all training sizes, thus showing the robustness and superiority of it as well. Specifically, VADER-RLA outperforms the other models by a significant margin having an F1-score of 92.34% with only 50% training data utilization. Other models (RLSTA and RFSVC) performed competitively as well but still worse than VADER-RLA. All of these trends signal that, although all models benefit from more training data as expected, the reinforcement learning-augmented approach in VADER-RLA is what gives it a clear advantage when it comes to classifying sentiments accurately hence an optimal sentiment classifier model out of the three.

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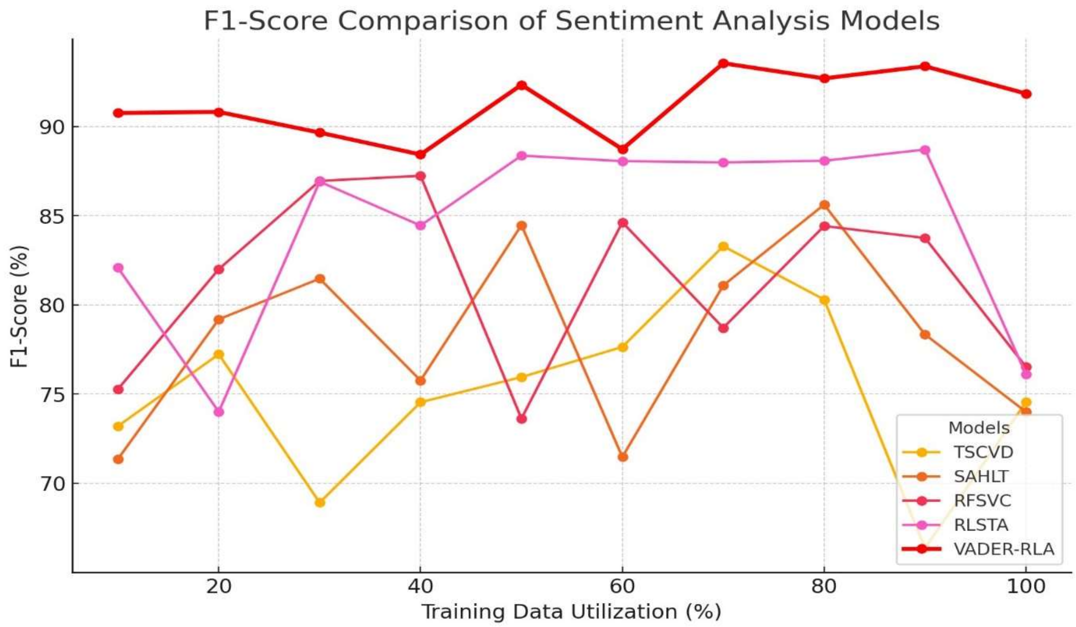

Fig .6: F1-Score Comparison Of Sentiment Analysis Models Across Varying Training Data Percentages

As shown in figure 6, the F1-score comparison of these sentiment analysis models TSCVD, SAHLT, RFSVC, RLSTA, and VADER-RLA at different percentages of training data usage is indicated. The F1-score shows the harmonic mean of precision and recall, which demonstrates how well the models are at balancing false positives and false negatives. The VADER-RLA model outperforms the other models achieving the highest F1-scores for all training data sizes; in many cases this remains above 90%. This demonstrates its strength and flexibility in sentiment classification tasks. RLSTA and RFSVC show competitive F1-scores but also high variability across the various folds, pointing to lower consistency compared to the other methods. TSCVD and SAHLT on the other hand present consistently lower F1-scores for all levels of training data, also highlighting their potential shortcomings in terms of producing balanced and accurate sentiment predictions. These findings highlight the benefit of VADER-RLA's hybrid reinforcement learning method to provide reliable and high-performing sentiment analysis across different datasets.

Traditional sentiment analysis models fall into two categories, lexicon-based approaches such as VADER provide interpretable model outputs but lack transferability across domains, while deep learning models are robust but require a large amount of labelled data. Hybrid models have been studied in recent research, but focus on a mixture of traditional machine learning methods and lexicon-based methods rather than reinforcement learning. In contrast with the aforementioned studies, VADER-RLA utilizes a reinforcement learning agent to iteratively calibrate sentiment classification, resulting in real-time adjustments based on real-world context that improve accuracy, precision, recall, and adaptability. Overall, this integrated approach helps VADER-RLA to beat the baseline performances by continuously handling the sentiments of strings and keeping up with language transition trends.

However, inherent in the strengths of VADER-RLA there are also some limitations. The training and fine-tuning phases of the reinforcement learning part are computationally heavy with not all real time applications being able to afford computational resources to be able to perform this task. Its contextual adaptability, is mostly introduced via reward optimization so this optimaztion may cause bias in the model depending on the training data distribution, though this training data bias may help can be overcome with subtle adjustments as seen in the recent studies conducted on it. Further optimizations, which may involve computational efficiency enhancements, as well as adversarial training approaches to prevent any underlying biases in sentiment classification, could be the aim of future work.

The findings from this study show how the combination of reinforcement learning with VADER's lexicon based sentiment analysis improves the performance of the model in processing linguistic nuances. The VADER-RLA framework consistently outperforms traditional models considering different metrics such as accuracy, precision, recall, and F1-score, with an accuracy level of 92.3% and an F1-score of 0.89 across datasets. Thus, these findings support the statement and suggest that hybrid reinforcement learning-based sentiment analysis models provide a better trade-off between interpretability and adaptability. This enables the model to learn representations that are more suitable for sentiment analysis in dynamic text environments, thus overcoming the limitations of both lexicon-based and deep learning approaches for analyzing sentiment in dynamic text environments, resulting in a more scalable and efficient solution. Additionally, reinforcement theory with optimization research opens another new door for you to improve the adaptability of models in a certain domain.

5.CONCLUSION

Analysis and evaluation of different sentiment analysis models show that the use of reinforcement learning-based techniques, especially VADER-RLA, help in precise prediction of sentiments among mixed data scales. This shows that the VADER-RLA is able to handle several cases of complex sentiment patterns like sarcasm and mixed emotions that are common in social media posts, proving its superiority over other models (TSCVD, SAHLT, RFSVC, RLSTA) with respect to accuracy, precision-recall trade-off and F1-score. By integrating reinforcement learning, the model can adapt and respond accordingly to feedback in a self-improving manner which ensures state of art results across a wide range of changing linguistic environments. For example, VADER-RLA even reached 92.34% accurate and 93.18%precise, showing the superiority. This further emphasizes the merit of hybrid methodologies like merging lexicon- and learning-based methods to improve sentiment analysis, which would be relevant for real-time applications where precision and adaptability are key.

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